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Activating Paralyzed Muscles using Adaptive Control and a Neuroprosthetic Technique

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Abstract- **Natural biological control involves the normal functioning of the living organism (i.e. human body) to regulate its parameters such that the vital functions are kept within the normal operating range. When this natural control fails, the biological feedback is unstable, operating under non-optimal conditions of the subject's vital capacity. In this context, ensuring the subject's nominal surviving capacity requires artificial control of the vital functions. Nowadays technology enables the development of artificial closed-loop devices to correct and provide the normal functions of the organism, thus replacing the damaged parts or helping to recover their natural properties. These procedures are called *rehabilitation techniques*. An application of closed-loop control will exemplify the importance of the challenges posed by a *neuroprosthetic* technique. Rehabilitation of drop-foot or hand-grasp movements with paretic or paralyzed skeletal muscles is achieved with the proposed self-adaptive auto-tuning control strategy.**

I. Introduction

The field of biomedical engineering is relatively young compared to that of control and automation and is one of the most remarkable in terms of interdisciplinarity. It has been known for many years that the biological world contains many feedback mechanisms and structures [1,2]. Consequently, a manifold of applications of classic and advanced control strategies to biological systems have been defined. Scientists applied their knowledge of mathematical modelling and system analysis to various areas of bio-medicine and identified those physiological functions not yet described in mathematical terms. This knowledge-information created a *playground* to control engineers. However, only nowadays has their work become meaningful, offering practical solutions to modern control problems.

The goal of this contribution is to give a practice-oriented overview of one of the *hot-spot* in biomedical control applications: artificial limbs. Such systems are usually nonlinear, constrained and their parameters vary in time. They are also highly dependent on developments in instrumentation and have a significant impact on the patient's life and consequently in society. Performance analysis of these systems is provided by control engineers as well as by physicians.

The proposed example is a paralyzed skeletal muscle that is controlled via functional electrical stimulation. An auto-tuning technique is presented along with its simulation results. A direct adaptive control (DIRAC) strategy is implemented in a discrete manner to simulate real-life practical implementation aspects. The simulation is made on a nominal 2nd order plus time-delay model of the skeletal muscle.

II. Artificial Electrical Stimulation of a Skeletal Muscle

Artificial electrical stimulation of neural tissue can be used as a neuroprosthetic technique to replace lost functions of the body. It is often referred to as functional electrical stimulation or, in particular, when used to stimulate neuromuscular tissue, as functional neuromuscular stimulation. Good overviews on this topic can be found in the work of Winters and Woo [3] and Stein et al. [4].

In order to apply artificial electrical stimulation to muscle, it is essential to take some basic physiological properties of the neuromuscular system into account; an introduction to this can be found in standard physiology textbooks [5]. In skeletal muscle, extrafusal muscle fibres are the primary unit of contraction. They are activated by axons of α-motoneurons, which originate in the spinal cord. In the neural system, transmission of information takes place in the form of impulse trains; the information is encoded in the pulse frequency. One motoneuron activates 5-1000 muscle fibres simultaneously. All fibres activated by the same motoneuron can be distributed over the entire muscle and form a motor unit, which represents the *unit* of muscle force in a normally innervated muscle. Two types of motor unit can be distinguished: fast and slow units. Slow motor units are more fatigue resistant and thus are able to generate a certain force for a longer time, whereas fast motor units can produce more power but with less endurance. The ratio of fast to slow motor units in a muscle has a great influence on its characteristics. All the motoneurons going from the spinal cord to the same muscle are contained in a nerve. Each motoneuron can be stimulated selectively by the central nervous system (CNS), enabling graduated muscle activation; those motoneurons which innervate slow fatigue-resistant motor units are recruited first, and fast motor units are only recruited if high force is necessary. The contractile force of each motor unit can be increased by raising the average frequency of action potentials. Artificial muscle activation can take place by applying electrical impulses to the motoneurons, thus generating action potentials which are transmitted to the corresponding muscle fibres. With current chronic implanted electrodes, single motoneurons are not stimulated directly. The electrodes are relatively large and stimulate many neurons.

Thus, with artificial electrical stimulation, muscle activation can be varied by (a) the energy of the electric pulse, which defines the number of recruited motor units, and (b) the pulse frequency, or the inter-pulse interval (IPI), which determines the contraction of the recruited muscle fibres. Because fast motor units have larger motoneurons, these units are recruited first, which is contrary to the way that the recruitment takes place when the muscle is stimulated by the CNS. Moreover, all the recruited motor units are stimulated synchronously, as opposed to the natural stimulation which can take place asynchronously. As asynchronous recruitment gives a smoother muscle contraction and, by allowing all muscle fibres some rest, the entire muscle fatigues more slowly.

Different types of muscle model are used for different purposes. The range extends from biophysical models, which are based on the structure and mechanisms of actual muscle, through analogue models, to purely mathematical descriptions. The most widely used biophysical model is the cross-bridge model, the basic principles of which were developed by Huxley [6]. This type of model is in principle useful to describe all characteristics of the muscle, as all model parameters are based on physical components, which makes it very popular amongst biologists. However, as this description quickly leads to large systems of nonlinear differential equations, it becomes very complex when the muscle as a whole or systems of muscles are considered. Also, the (microscopic) parameters of the Huxley-type model are not easy to interpret in terms of macroscopic muscle characteristics. In biomechanics, analogue models remain more popular, as they are more tractable and easier to interpret when used to describe an entire muscle. The most often cited model is based on Hill's [7] description and comprises a contractile element, which is the force-generating element, in parallel with a spring, representing the elasticity of the muscle (and the tendon, if included), all of which is in series with a second spring representing the passive tissue. Although all elements of this model are related to macroscopic behaviour of the muscle, special experiments are necessary to identify their values for specific muscles. In its current form, the Hill-type model is not always valid; for example, very fast muscle contraction cannot be described satisfactorily.

For use in implantable muscle stimulator devices, other model characteristics become important. The model should be easy to adapt to the muscle using data from standard experiments which do not damage the muscle tissue. Also, the model (or the controller based on it) must not be computationally expensive, as it should be implemented as a microcontroller. For that reason, most real-world implementations are based on simple linear muscle models. Often, the contraction is assumed to be isometric, which gives a single-input (stimulation) single-output (force) system. Experiments have shown that a second-order dynamic linear model with delay can be applied [8]. To take the nonlinear recruitment of motor units into account, the linear structure is extended by a nonlinear static recruitment curve, which leads to a Hammerstein model. However, such a model does not take nonlinearities due to varying IPIs in the stimulation patterns into account [9].

III. Paralyzed Skeletal Muscle Control

When considering the physical requirements of the control system, a set of time-domain specifications will result. In the task of interest here - locomotion, the desired activation of the muscle can be described as a stepwise signal. The amplitude of the activation will be constant. However, the period of the stimulation will vary, depending on the required level of supporting force at any time; e.g. during periods of more intense physical activity, the activation period will be longer. The frequency of the desired activation will also be variable.

The actual activation of the muscle, as achieved through feedback control, is required to meet the following specifications:

(i) a reasonable rise time,
(ii) no overshoot, and
(iii) zero steady-state error.

In addition, this performance and closed-loop stability should be robust to expected variations in the controlled muscle dynamics – since paralyzed muscles are often subject to rehabilitation techniques. Therefore, artificial control of paralyzed or paretic muscles is an important research topic, stimulated by the advances in technology and instrumentation. One of the latest research outcomes in this area is the use of functional electrical stimulation (FES) to produce force in a skeletal muscle control loop [10].

A DIRAC (DIRect Adaptive Control) control strategy is the subject of this feedback-control application study. The DIRAC algorithm is both an auto-tuning as well as an adaptation method for the controller parameters. Since paralyzed or paretic muscles are time-varying systems, an adaptive/auto-tuning method is therefore justified. A simple simulation on a muscle model adapted from the literature is performed and the controller performance for reference tracking is depicted. A comparison between a classical control approach (PI and PID) and a DIRAC-PI controller is given in [11]. The study in [11] includes some implementation aspects of a 2^{nd} order model, *without considering time-delay.*

A. Simplified Muscle Model

For linear dynamic systems, the dominant time constants and the dynamic order can be extracted from its step response. Based on this information, estimates for the optimal sampling period and the model structure are possible. Owing to the physiological properties of muscle stimulation, its input signal must be pulse-like and, hence, the system's step response cannot be measured directly. Using experimental data, Gollee and Hunt [9] extracted the impulse response from which the step response was derived by integration. A linear model capturing the properties of a muscle under isometric conditions can be represented by a 2^{nd} order transfer function with time-delay [12].

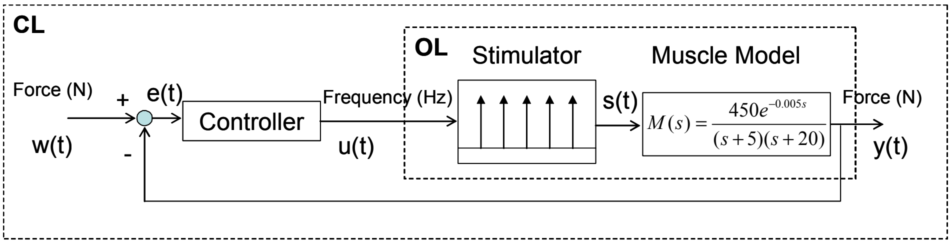

Figure 1. Block scheme of muscle model simulation (open loop OL and closed loop CL configuration)

$$M(s)=\frac{450e^{-0.005s}}{(s+5)(s+20)} \quad (1)$$

The parameters (450; 5; 20; 0,005) are a set of *nominal* parameters and their value can change (considerably) from person to person. These parameters depend on the physical condition of the muscle, age *etc*. In the case of a paralyzed muscle, important variations are observed during the rehabilitation period. The time delay (5ms) has been taken into account and is the time between the nervous activation and the calcium release in the muscle in order to obtain contraction.

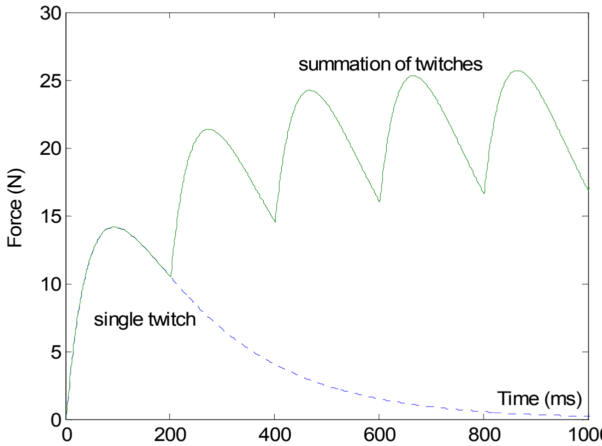

Figure 2. Single Twitch (dotted) and Summation of Twitches (continuous) at 5Hz (unit) impulse frequency in open loop.

The input to such a model is a stimulus which occurs with a certain frequency and the output is the force resulted from the contraction of the muscle, as in Figure 1. The input frequency is limited to 5Hz – 50Hz (the frequencies for which the static characteristic is linear).

From a mathematical standpoint, the response *y(t)* of the process M(s) to an input $u(t)$ (= frequency *F*) is the effect of a series of impulses with period *T* (= *1/F*) applied as input.

A simple experiment (unit impulses) depicted by Figure 2 shows the output of the process corresponding to (1) and having the time constants: 1/20=50 ms and 1/5=200 ms, a total open-loop settling time of about 1 second.

B. A DIRect Adaptive Controller (DIRAC)

Controller design is based on the use of the auto-tuning principle, which automatically finds a set of PI(D) parameters without an *a priori* process identification (i.e. no model required). A brief description is provided in this section and more details can be found in [13].

The PI(D) parameters can further be used in a discrete-time control scheme, with a software implemented controller:

$$u(t)=u(t-1)+c_0e(t)+c_1e(t-1)+c_2e(t-2) \quad (2)$$

with the error being the difference between the desired force w(t) and the measured force y(t):

$$e(t)=w(t)-y(t) \quad (3)$$

Denoting the shift-operator: $q^{-1}e(t)=e(t-1)$, results:

$$u(t)=\frac{C(q^1)}{1-q^{-1}}e(t)=\frac{c_0+c_1q^{-1}+c_2q^{-2}}{1-q^{-1}}e(t) \quad (4)$$

and the control loop is depicted in Figure 1.

As De Keyser [13] mentioned, “the DIRAC algorithm can be considered as an auto-tuning as well as an adaptation method”. Indeed, since the identification of the controller parameters is done within the DIRAC strategy, there is no need for specifying a model of the process *a priori*, thus functioning as an *auto-tuning* method. Secondly, if used *on-line*, the PI(D) parameters are adapted continuously, thus resulting in a direct *adaptive* controller. The use of auto-tuning or adaptive control seems appropriate for the control of skeletal muscles, since they are known to be time-varying. The adaptive control method described in this section is easy to understand and simple to apply. In the context of an unknown process model, the assumption that the muscle and the stimulator are described by an unknown (discrete-time) transfer function $MS(q^{-1})$ leads to the closed loop transfer function:

$$y(t)=\frac{C(q^{-1})M_S(q^{-1})}{(1-q^{-1})+C(q^{-1})M_S(q^{-1})}w(t) \quad (5)$$

The *design performance* of the closed loop is specified by a *reference model,* $R(q^{-1})$, given *a priori*. For example, one of the desired characteristics of the closed loop response can be the settling time. The task of controller tuning is to find $C(q^{-1})$ (i.e. c_0, c_1 and c_2) such that the closed-loop transfer function from (5) should approximate the desired reference model $R(q^{-1})$. This can be written as:

$$C(q^{-1})(1-R(q^{-1}))M_S(q^{-1}) \cong (1-q^{-1})R(q^{-1}) \tag{6}$$

Applying (6) to the time-signal $u(t)$, results in

$$C(q^{-1})(1-R(q^{-1}))\underbrace{M_S(q^{-1})u(t)}_{y(t)} \cong \\ (1-q^{-1})R(q^{-1})u(t) \tag{7}$$

and becomes:

$$C(q^{-1})(1-R(q^{-1}))y(t) \cong (1-q^{-1})R(q^{-1})u(t) \tag{8}$$

Defining the filtered signals:

$$\begin{aligned} u_f(t) &= (1-q^{-1})R(q^{-1})u(t), \\ y_f(t) &= (1-R(q^{-1}))y(t) \end{aligned} \tag{9}$$

and introducing the error signal $\varepsilon(t)$, (8) becomes:

$$\boxed{u_f(t) = C(q^{-1})y_f(t) + \varepsilon(t)} \tag{10}$$

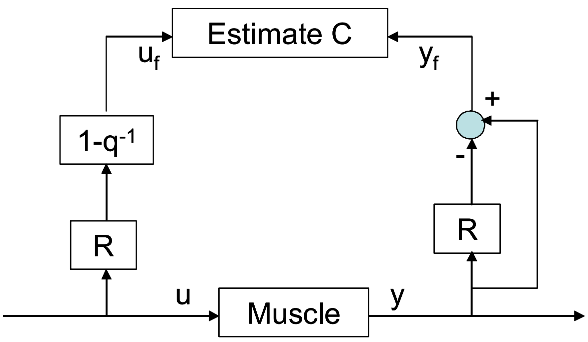

Figure 3. Scheme of the DIRAC Strategy

The final step is to estimate (e.g. via least-squares estimator) the parameters in the polynomial $C(q^{-1})$ such that the errors $\varepsilon(t)$ are minimized. The overall scheme is presented in Figure 3. Notice that for the simulation presented in this contribution, DIRAC algorithm has been used *off-line* for initial tuning of a PI controller; nevertheless, the method can easily be implemented *on-line* as a direct adaptive controller.

The DIRAC-PI controller parameters applied in this case are: K_p=0.00623 and T_i=0.01, with a sampling period of T_s=10ms.

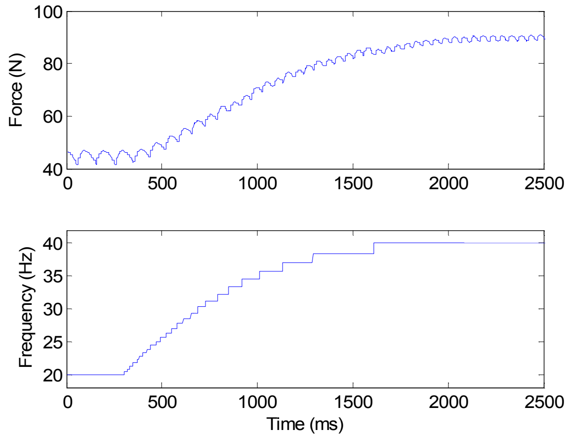

Figure 4. A closed loop response with a DIRAC-PI controller

IV. Performance Analysis

The experiment consisted in *changing the reference set-point* force from 45N to 95N. On a scale of 22.5N-225N, a set-point change of 50N is about 25%. The result given by the controller is depicted in Figure 4 along with its corresponding control input. It can be observed that the control performance meets the specifications mentioned in Section 3. With a very small overshoot, the output force goes to the desired set-point value of 95N with zero steady state error. Controller output - frequency - stabilizes at the value of 40Hz. Taking into account that the muscles to be activated are paralyzed muscles, a smooth convergence to the set-point force value is more justified than a fast and aggressive convergence, thus avoiding damage of its mechanical properties and supporting its rehabilitation procedure.

The application of adaptive control techniques for skeletal muscle control is motivated by the time-varying character of the system (i.e. in rehabilitation systems). Earlier studies have shown similar performance of the adaptive control strategy with a controller designed based on the model of the system [11]. However, the obvious advantage is that the DIRAC strategy does not require an *a priori* knowledge of the model. It can also be used *on-line* and implemented in discrete time. Its adaptive nature tackles the problems imposed by time-varying systems.

An interesting challenge is posed by the software implementation of such a discrete time stimulus. If some conditions for numerical accuracy (timing) are not respected, the results are strongly influenced (Figure 5). A more detailed description of this phenomenon and a proposed solution is given in [11].

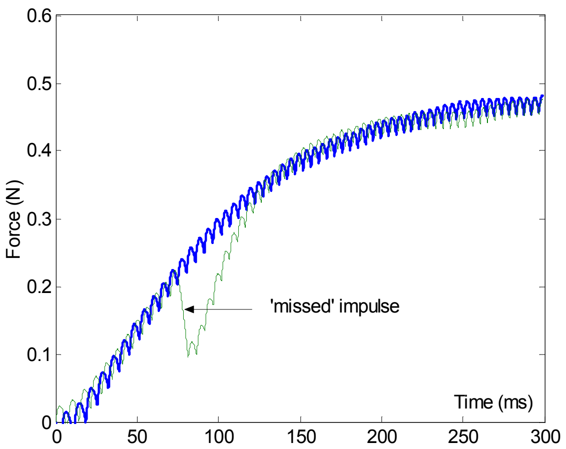

Figure 5. Effect on results of the numerical errors in the stimulus function

V. Conclusions

One issue that complicates biomedical control and poses modelling problems is the significant inter- and intra-patient variability observed. Therefore, a key component in a control system is the adaptive element. Although it is more difficult to guarantee stability and performance levels for these systems than for static control algorithms, the ability of the algorithm to adapt to a patient's specific behaviours may lead to remarkable performance improvements.

The use of *adaptive and auto-tuning control strategies* such as DIRAC in closed-loop control of paralyzed skeletal muscles is justified by *inter-* and *intra- patient variability*. The muscle properties differ from person to person, as well as from one time-interval to another. Comparable results can be obtained either with or without knowledge of a muscle model [11]. This means that a wearable device can be supported, applied and used successfully on any patient, due to the auto-tuning and adaptive properties of the DIRAC control strategy. The elimination of the identification step considerably simplifies the control task. Taking into account the time delay present in the system is important for real life applications and satisfactory and stable results are obtained.

The present contribution has given a brief overview of the practical problems posed to a control engineer by this application. The task of developing stable and robust control algorithms is not limited to a simple mathematical description. Real-life constraints and hardware/software limitations are to be tackled in an optimal manner, providing a feasible, practical oriented solution.

Although more advanced control can be applied to this example, it may hold significant disadvantages. For example, an important drawback is the need for a model in the prediction algorithm when a model based predictive control strategy is applied. The aim of this presentation has been limited to a simple but satisfactory solution: an auto-tuning algorithm that does not require the identification of a model. However, in this case, a model is needed for simulation purposes. Performance is discussed from practical and academic standpoints. A more technical description of the implemented algorithms is provided by use of referenced publications.

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